How does debate influence policy? While studies show that framing and narrative structure influence attitude formation and policy opinions, there is mixed evidence as to whether and how they influence policy outcomes. I propose that debate — the distribution of all frames used and the volume at which it is projected — provides the criteria by which policy options are compared. In turn, the evaluative criteria determine which pieces of legislation are viewed as good or bad policy and politics. I hypothesize that as debate on an issue increasingly changes, then policy will change to a greater degree. To test this, I first measure the debate in Congress on nineteen issue areas using the Congressional Record — speeches given on the floors of the House and Senate. I do so using dynamic topic models. Then I determine the degree of change in policy ideas by estimating the change in policy ideas proposed and passed as legislation in Congress. This is done using a ratio matching algorithm, which produces a measure indicating the degree of similarity in text across successive Congresses using methods analogous to plagiarism detection. Using these two measures, I show that as debate on an issue changes, the policy ideas passed into law also change. This study provides a new way of measuring the effects of framing and a new tool to study the causes of policy stability and change. Additionally, I provide a new framework to understand how frames influence policy by developing a new measure of debate change.
Narratives and the information contained within them have power. They structure how we think. They tell us whether something is a problem. They tell us what problems need attention. They tell us what solutions should be connected to those problems. Studies of individuals bear out these claims; they show that narratives and frames influence attitude formation and response to different stimuli (Berinsky & Kinder 2006, Chong & Druckman 2007, Entman 1993). However, evidence is mixed as to whether narratives and frames influence policy change and outputs. For example, contrast the discussion of the lack of effect that framing the estate tax as a “death tax” had as discussed in Bartels (2009), with evidence put forward by Baumgartner, De Boef & Boydstun (2008) demonstrating that re-framing the death penalty drastically changed policy outputs. In the first, framing appeared to have a limited influence compared to changes in the presidency and party composition of Congress, whereas in the second the increased focus on the innocence frames decreased the number of people sentenced to death. Additionally, these studies typically attribute policy change to the influence of a specific frame or set of frames. As a result, skeptics might ask whether these studies are constructing ad hoc fallacies that are not generalizable instead of tracking and explaining a systematic macro-level process.

For example, compare debate surrounding health care under former President Clinton and former President Obama; efforts at reform failed in the 1990s but succeeded in the late 2000s. In the 1990s, while the debate began focused on the growing costs of health care and growing gaps in coverage, opponents of the proposed reform shifted the debate to focus on the role of government and the political nature of the process. The dominance of this latter frame was epitomized in the Harry and Louise television advertisements, where a couple discussed the complexity of the plan and growing bureaucratic red tape (Annas 1995, Braun 1995, Clymer, Pear & Toner 1994). Ultimately, the proposal failed to even come to a vote. However, in the late 2000s, a greater proportion of the debate focused on the the growing uninsured rate at that time and the suggested policy proposals to address the problem. Once again, this trend was epitomized when Harry and Louise returned to discuss the proposed health care plan;
this time they discussed the need for coverage. Ultimately, the plan passed as the Affordable Care Act (Foster, Tanner, Kim & Kim 2014, Gay-Stolberg & Herszenhorn 2009, Staff 2010).

At the same time the debate changed, the composition of the House and Senate changed. The government was divided in the first episode but unified in the second, the nation faced the greatest recession since the great depression, and the distribution of interest group preferences changed. Researchers studying policy change in Congress (Aldrich 1995, Cox & McCubbins 2005, Baumgartner & Jones 2010, Mayhew 2005) and the influence of interest groups in Congress (Gray, Lowery & Benz 2013, Grossmann 2012, Hall & Deardorff 2006, Baumgartner, Berry, Hojnacki, Leech & Kimball 2009) have repeatedly shown that these and other differences affect policy proposals and the passage of legislation. This question arising from this is: did debate — the frames used and volume at which the debate was held — influence outcomes beyond what the changing political and economic climate would predict?

In more general terms, I ask: 1) does debate change policy; and 2) why does debate about legislation influence policy change — the success or failure of legislation? Additionally, I question whether change is due to the use of specific frames or the entire collection of those used. I propose that debate shapes policy by determining priorities when evaluating policy proposals nested within legislation. Within Congress, this typically follows four general steps. First, those invested in a given issue area divide into two “teams” — those wishing to change the policies related to a given issue area and those wishing to keep them the same. Those not invested form a third group of marginal legislators that may be swayed. Second, each side amasses resources and forms strategies to pursue their interests. Third, they begin to debate the issue. Debate is defined by its structure — the sum of the information, arguments, and frames put forward by both sides — and the space it occupies — the volume the debate is held at. It sets the evaluative criteria for proposed legislation. This criteria is then used to determine whether proposed legislation is relevant and whether it should be passed into law. Eventually, this leads to policy change or not.
Here, I focus on testing the connection between debate and outputs. Specifically, I hypothesize that as debate changes, the policies enacted also change. In the health care example, the emphasis shifted from a hyper focus on politics and the role of the federal government to a more equitable division between those concepts and whether the proposed policy would decrease the number without health insurance. In addition to the changes in the political and economic environment, the change in debate resulted in a failure for Clinton and a win for Obama.

To test whether changing debate systematically influences policy change, I measure the extent to which the debate on an issue changes from one Congress to the next using Congressional floor speeches. Debate — the sum of frames used and attention captured by it — within the speeches is identified using dynamic topic models. The change in volume is measured as the percent change in number of speeches given. Change in policy ideas proposed and passed is regressed on this. Change in policy ideas are measured by determining how similar the language of the bills proposed in a given Congress are to the previous one. Additionally, I control for change in party control of the House and change in party control of the Senate. I use fixed effects for policy area and random intercepts for Congress.

In the course of developing and testing this theory, I make two contributions. First, I show that debate influences the degree of policy change by constraining what is used to evaluate legislation. In doing so, I underscore the importance of not only looking at party, alliances between legislators, or the distribution of resources but also of what is being said. Second, I provide a new way of measuring the effects of framing and a new tool to study the causes of policy stability and change. Thi is important because up to this point measures of how we talk about issues have been limited to measures of tone and topic. However, many theories suggest that the frames themselves and how they are used in conjunction with each other matter.
Changing Frames to Change Policy

Often, policy change is a long and messy process. There are many places where people may interject and many points where random events can alter outcomes. While the process is frequently messy and cluttered, it can be collapsed into four broad stages. First, the political actors involved and concerned with a given issue area form teams, which arise relative to the enacted policies as they stand — the status quo in that issue area. Typically, two broad teams are formed and can generally be classified as those protecting the status quo and those pushing to change it. One team desires changes while the other desires no change. However, not all legislators actively engage in every debate. This leaves a third group outside of the process but affected by it: the unaligned and marginal legislator who may be swayed. Next each team amasses resources and forms strategies to elicit their desired change. Resources and strategies are used to construct the debate over policy alternatives. Third, those wishing to change existing policy introduce and debate legislation as it moves through the process. Finally, debate informs how members of Congress evaluate the proposed legislation. This in turn influences whether policy changes or not. Then the process restarts. Figure 1 summarizes this process.

Exploring, explaining and testing the mechanisms and transitions between each step is an immense task. Isolating connections between steps spans multiple literatures and decades of study. In Figure 1, The gray box denotes where the status quo policy is located; outside of this box is where it may be changed. The feature of this figure that has yet to be discussed is the dotted lines surrounding debate structure and policy change. The remainder of this section presents a theory connecting these two boxes. However, before moving onto how frames and debate structure influence policy, we need to better understand what constitutes an issue debate.

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1Throughout this process, I do not assume that either team necessarily wants to find the best possible policy nested within a piece of legislation. Rather, I simply assume that they either do or do not want the policy change that has been proposed in any given piece of legislation under consideration.
Where Does Framing Fit In?

Connected to every issue (e.g., health, education, crime) is a debate made up of the frames used by each side. A debate is defined by both its internal structure and how much space it occupies in the broader discourse. Debate structure is the sum of the frames invoked by individuals and groups participating. Frames are specific dimensions of consideration invoked by specific words, terms, and phrases that set the bounds of discussion. How often and in what way attributes are invoked structures the preferences of those participating in the debate and those listening to it. The debate structure narrows a possibly infinite set of considerations to a smaller set. This occurs because frames highlight or emphasize certain dimensions, while non-use of a frame results in other dimensions being ignored. The relative rate of use of a certain frame shapes how much that related evaluative dimension should matter; it sets the weight of that consideration. Additionally, how much space the debate occupies in the broader agenda — the volume it is held at — influences who hears the debate and how many outside people must pay attention to it: the louder it is, the greater the number of those outside of the debate who will listen.

Using these evaluative criteria, each piece of legislation is considered and evaluated.
these criteria are on average favorable towards a policy change or a piece of legislation, then it will pass. If not, it will not pass (Jones 1994, Jones 2001). When comparing outcomes between periods, the starkest change occurs when someone introduces a new frame and thus induces a heresthetical change (Riker 1986). However, the same effect can be seen in a redistribution of attention across frames between periods (Baumgartner & Jones 2014, Jones 2001). In each case, the marginal legislator (not directly involved in the debate) might be moved. As the marginal legislators shift, then policy change may occur.

For example, consider again differences in the health care debate in the 103rd (1993/1994) and 111th (2009/2010) Congresses. While there were many possible frames the White House and members of Congress could have chosen to use, only a few in each time period actually were used. Here let us simplify the debate to the rate of use of four frames for the purposes of illustration: playing politics, the role of the federal government, the cost of health insurance, and the number without insurance. The relative use of the frames forms evaluative weights on each dimension: use determines how much credence should be given to each dimension. Theoretically, in the 1990s, the relative weights might have been approximately 65%, 2%, 30%, and 3% respectively. In the late 2000s, these may have been approximately 48%, 5%, 30%, and 17% respectively.2

These frames and their relative use are seen in Table 1. The first column shows the hypothetical framing weights in the debate surrounding Clinton’s proposal. The second column shows the hypothetical framing weights in the debate surrounding Obama’s proposal, the ACA. The third column shows the real change in these weights. Finally, the fourth column shows the absolute change in these weights. As can be seen, use of the playing politics decreases by 17 points, while the use of the number of uninsured increased by 14 points. To find the change in debate structure, the absolute difference between the two periods for each frame is found and summed. The result is a change of 34 points.

These weights follow those found in the Pew content analysis of the media coverage of the health care debate in each period (Staff 2010, Clymer, Pear & Toner 1994). These numbers are loose correlates, because the coding scheme for frames was not the same in each report.
Table 1: Change in Framing Weights in the Health Care Debate between Proposals

|                        | Clinton | Obama | Δ(Weights) | Σ(|Δ(Weights)|) |
|------------------------|---------|-------|------------|----------------|
| Playing Politics       | 65      | 48    | -17        | 17             |
| Federal Government     | 2       | 5     | 3          | 3              |
| Cost                   | 30      | 30    | 0          | 0              |
| Number of Uninsured    | 3       | 17    | 14         | 14             |
| Total                  | 100     | 100   | 0          | 34             |

Thus the debate structure — composition of frames used — determines how policies will be evaluated. However, while this discussion shows how what is said may inform policy evaluations by members of Congress of pieces of legislation, a question about the process lingers. How does framing influence policy outcomes?

**Debate and Policy**

Debate on an issue influences policy by structuring the set of policies to be considered and setting the evaluative criteria used for each policy proposal for a given issue area. To directly effect policy change, debate must occur in an appropriate venue. Here I discuss (and test) this within Congress. However, this process is not limited to a single institution or level of government. Rather, it is a general theory on the production of policy if some debate occurs. In this paper, I focus on connecting debate to policy; discussion of why members of Congress and parties choose the frames they do is outside of the scope of this paper. Within this context, where does debate influence legislation in the US Congress?

Additionally, I assume in any single Congress $t$ there are three general groups: status quo preservers, status quo challengers, and the unaffiliated who can be swayed. As a result, there are two teams debating policy and up to $n$ actors who choose which of $k$ frames to tap in the statements they construct and in framing their arguments. Teams can use multiple frames, and they can overlap in their usage. By overlap in their usage, I mean both that multiple speeches may use the same frame, but also that speeches given by both teams may use the same frame. Such actions may be motivated by recent findings that suggest the
best counter frame is, in fact, a frame of the same type. For example, moral frames may
best counter other moral frames (Clifford & Jerit 2013, Jerit 2008), and strong frames may
counter strong frames (Wang, Beauchamp, Shugars & Qin 2017, Druckman, Peterson &
Slothuus 2013). The overall and relative use of these attributes by members of each team
participating in the debate amounts to the debate structure.

First, legislation is introduced. Typically, those seeking to change the status quo do
this. However, at some points those seeking to maintain the status quo must introduce
legislation, such as with sunset legislation or when budget bills. Regardless, this pushes the
process into its next phase: debate. In Congress, debate is constructed by what is said on
the floors of each chamber, in committee, and behind closed doors. Debate participants
construct debate through their use of frames and by allocating attention to the issue. When
constructing the debate, those pushing for change and those trying to block it focus on the
frames that they believe are most likely to sway the margins. Finally, whoever wins over
the marginal legislators succeeds in their goal: either the status quo changes or it does not.
For example, in debates over health care in the summer of 2017, Democrats focused on
the predicted rise in the number of uninsured citizens and loss of care for citizens, while
the various Republican factions pushing for a repeal of the Affordable Care Act (ACA)
highlighted that they promised to get rid of the policies the ACA put in place. Seemingly,
the focus on policy rather than politics swayed enough Republicans to block any repeal

While the effect of frames on policy outcomes has been discussed as if it is static up
to this point, it is cyclical as seen in Figure 1. Many iterations in the policy production
process occur in any given issue domain. The initial debate is set by the first pass through
the cycle. Each successive pass may or may not see a change to the debate structure used
in the previous cycle. As a result, the connection between debate and legislative outcomes
can either be understood by connecting specific frames to policy debates and evaluating
the effect of each on the outcome, or the change in debate can be related to the change in
policy as proposed in legislation. The hypotheses proposed and tested here come from the latter, and answer the question: How does a change or lack of change in the debate structure associated with an issue influence policy outcomes?

If there is a change in an issue debate, then the policies considered and passed change, because how they are evaluated changes. As the dimensions of evaluation change, the distribution of marginal legislators changes. If there is a small shift in debate structure, then the policies considered and passed will either minimally change. If there is a large shift in debate structure, then the policies considered and passed will change to a greater extent. Put simply, as debate changes, policy also changes.

**Hypotheses**

Two types of observable implications follow from this theory. First, a necessary condition for policy outputs themselves to change is that the policy ideas undergirding them change between Congresses. This form of change appears as new solutions to problems that may induce different levels of real change in outputs. Second, the policy outputs themselves may change, such as a change from what is in the revised code or as changes in the budget. In this paper, I focus on the first: the change in policy ideas. There are the only two stages in the process that all bills may go through, when looking across Congresses: their proposal and final vote. Two hypotheses are produced based on these two stages. These are:

**H1:** As change in debate increases between the previous and current Congress, then similarity in policy ideas in legislation proposed decreases.

**H2:** As change in debate increases between the previous and current Congress, then similarity in policy ideas in legislation passed decreases.

While debate is staged around what is proposed to some extent, it also influences what will be proposed in that Congress by highlighting different aspects of the issue and changing how the issue is considered. As a result, differences in what is proposed in the current versus previous Congress still indicates a change in policy ideas proposed.
Measuring Debate Structure and Policy Change

To test these hypotheses, I focus on policies proposed and passed in the 104th (1995/1996) through the 112th Congress (2011/2012) across all issue areas which data allow. The time span is chosen to range from the 104th through the 112th Congress to accommodate data limitations; the text of the Congressional Record is not available electronically before 1995, the start of the 104th Congress. I use the Comparative Agenda’s Project’s (CAP) definition and classification policy issue areas to identify the areas used here. CAP is a collaborative project looking over time and across countries that “... classifies policy activities into a single, universal and consistent coding scheme” (http://www.comparativeagendas.net/pages/About). I include 19 of the 20 areas that are included in their major policy topic codes; data limitations preclude the inclusion of the immigration policy topic. The issue areas included in the analysis are: macroeconomics, civil rights, health, agriculture, labor and employment, education, environment, energy, transportation, law and crime, social welfare, community development and housing, banking and domestic commerce, defense, science and technology, foreign trade, international affairs and foreign aid, government operations, and public lands and water management.3

To conduct the analysis, I create a unique dataset comprised of the text of 88,259 Congressional bills and 129,763 speeches from the Congressional Record. The dependent variable is the degree of policy change in proposed legislation and the degree of policy change in passed legislation between Congresses and within a given issue area. The main independent variable is the extent of change in debate structure as observed in the Congressional Record between Congresses within a given issue area. To measure each, the relevant text (bill text and the text of floor speeches) are used. Below, I discuss the data used, the construction of each measure in greater detail, and then briefly discuss the controls.

3For more information on the general coding scheme and definitions, see the CAP website at http://www.comparativeagendas.net/.
Measuring Proposed and Enacted Policy Change

Proposed and enacted policy change is measured as the change in the content of the legislation. Because language in legislation is highly structured and constrained, plagiarism detection techniques can be used to identify not only strict plagiarism between bills, but also the more subtle transfer of policy ideas (Wilkerson, Smith & Stramp 2015, Garrett & Jansa 2015, Linder, Desmarais, Burgess & Giraudy NP). As a result, change in policy ideas between Congresses is measured as the average amount copied in bills in a given policy area. Data for this comes from two places. I scraped the text of each bill included in the analysis from Congress.gov. The policy codes come from the Congressional Bills Project,\(^4\) which uses the CAP policy coding scheme allowing it to be easily compared to other aspects of the Congressional agenda. The result is a corpus of 88,259 bills.

A single bill may borrow from a portion of another piece of legislation or another bill in its entirety. The borrowed portions may either be incorporated as a small section of the new piece of legislation or become the entire piece of legislation. As a result for this analysis, a directed similarity function is used to accommodate this. Specifically, I use the a ratio of matches calculation. The function finds the ratio of the number of strings of terms in document \(B\) that are also in document \(A\). The result is a number between 0 and 1, where 0 indicates no shared content and 1 indicates that document \(B\) only contains content from document \(A\). Mathematically this is:

\[
M(A,B) = \frac{|A \cap B|}{|B|}
\]

The change in policy ideas in a given Congress is calculated by comparing all bills in a given issue area in that Congress to those in the previous Congress. When computing similarity, strings of five words (5-grams) are used.\(^5\) Then a single similarity score is assigned

\(^4\)E. Scott Adler and John Wilkerson, Congressional Bills Project: 1993 to 2012, NSF 00880066 and 00880061. The views expressed are those of the authors and not the National Science Foundation.

\(^5\)Other than n-gramming, no other preprocessing is done to the text.
Table 2: Summary of Average Similarity of Policy Ideas Between Congresses

<table>
<thead>
<tr>
<th></th>
<th>Min.</th>
<th>Mean</th>
<th>Max.</th>
<th>SD</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed</td>
<td>0.33</td>
<td>0.48</td>
<td>0.62</td>
<td>0.06</td>
<td>171.00</td>
</tr>
<tr>
<td>Passed</td>
<td>0.10</td>
<td>0.30</td>
<td>0.71</td>
<td>0.09</td>
<td>171.00</td>
</tr>
</tbody>
</table>

to each bill in the given Congress; the maximum ratio of matches is used for each bill. The maximum is used, because this better captures the idea of reused and repeated ideas. Additionally, if this introduces any bias into the measure, it is against finding what I have hypothesized, because it biases the measure towards less variation and higher values. Thus making it a harder test of the theory. After a single score is assigned to each bill, the mean is taken for the issue area for that Congress. The result is a single score ranging from 0 to 1 for an issue area within a Congress. For additional information and examples about the measure and this process, see the appendix. Figure 2 presents what these scores look like for a single policy area: health. To see graphs of every issue area, see the appendix. Table 2 presents a summary of these scores.

In Table 2, the summary statistics of the two dependent variables are presented. The first column shows the minimum value the measures can take, the second column shows the mean value the measures can take, the third column shows the maximum value the measures can take, the fourth column shows the standard deviation of the measures, and the last column shows the number of observations for each variable. From this table, two observations can be made. First, the ideas proposed are more similar on average to those in the previous Congress than those passed. Second, there seems to be greater variation in degree of shared policy ideas among those passed than those proposed.

In Figure 2, the y-axis shows the degree of copying, and the x-axis shows the Congresses. As the values on the y-axis increase, the more similar the policy ideas in that Congress are with the previous one. The vertical line indicates the 111th Congress (2009/2010) when the ACA was passed. Two important takeaways from this figure is that change in policy ideas varies over time and by stage of the legislative process. The first conforms to what we expect
to see based on case studies and histories of policy over time, such as seen in the evolution of economic policy presented by Smith (2007). The second second highlights what we may have suspected before but has been little studied.

Additionally, we can see that the trends observed in the calculated measure match intuitions we might have about how similar health policy legislation in each Congress was to the one that came before — specifically where we observe the Affordable Care Act (ACA). The ACA was lauded as a policy innovation that overhauled the federal health care system. As a result, we would expect the Congress that passed the ACA to have a low similarity with the previous Congress (have a low score) for passed legislation. Additionally, in the Congress following the passage of the ACA, we would expect to see many bills similar to those proposed in the previous Congress but never reported out of committee or passed. This is because many members of Congress proposed legislation to repeal the ACA, which were never passed into law. Both of these trends are observed.
Identifying and Measuring Debate

I measure debate change using speeches given on the Congressional floors and logged in the Congressional Record. While this is only one of many venues where speeches given informs debate on an issue, I use this source because it includes a variety of different types and styles of speech, is reflective of the coordinated policy making in Congress either through the caucuses or the parties, and is reliably and readily available back to 1995. I scraped all the speeches available from the Government Printing Office. To be able to compare debate structure found in the speeches to policy ideas in the bills, congressional speeches need to be coded for issue area discussed according to the same scheme.

To do this, I first merge in policy codes from Tyler Hughes’ (2016) data set of one minute speeches for all of the one minute speeches given on the House floor. One minute speeches are short speeches given by anyone in the House and are not constrained by policy topic to be discussed or manner of speaking about the issue. Party leaders, party loyalists, mavericks within the party, and extremists all give one-minute speeches (Harris 2005, Morris 2001, Maltzman & Sigelman 1996). This means that they span the set of possible topics and the ways in which issues may be discussed in a given Congress. Next I build a supervised learner using this already known policy codes. Supervised learning is the machine learning process of using a labeled set of documents (here the labeled one-minute speeches) to generate a model that can predict the labels assigned to those documents. The resulting model can be used to predict the labels of previously unseen documents (here the rest of the Congressional Record). I then use this learner to apply policy codes to the remaining unlabeled speeches that could possibly be on a policy topic (not all floor speeches discuss policy rather some are quorum calls, the morning prayer, etc.). I can do so because of the highly structure nature of the speeches: they typically are constrained to be about a single topic or bill, follow the same format, and are under greater control of the messaging teams of both parties (Oleszek 2013).

The result of all of these steps is a corpus of 129,763 policy speeches given on the floors of Congress. Over the time period, the average number of speeches given about a specific issue
area is 6,488, and ranges between 1,735 speeches (agriculture) to 19,314 speeches (macroeconomics). For more information on this process, see the appendix. Using these, I then measure structure and volume separately. To fully capture debate, these are then combined into a single measure.

Change in volume is measured as the percent change in the number of congressional speeches given on that issue between a given Congress and the preceding Congress. Negative values indicate the number of speeches decreased, positive values indicate that the number of speeches increased, and values of 0 indicate that no change occurred. Effectively, these values possibly range from -2 to 2; a decrease of 200% to an increase of 200%. A summary of these rates are presented in Table 3. As can be seen, change in volume ranges from -0.75 to 1.85 and has a mean of 0.

While volume can be calculated in a single step, the process of measuring change in frame use is less straightforward and proceeds in three steps. First, I identify frame use by Congress and by issue area. To do this, I use dynamic topic models (DTM) via non-negative matrix factorization (NMF) developed by Greene & Cross (2017). This modeling approach is used rather than either a structural topic model (Roberts, Stewart, Tingley, Lucas, Leder-Luis, Gadarian, Albertson & Rand 2014) or latent Dirichlet allocation (Blei, Ng & Jordan 2003, Grimmer 2010), because it directly models the dynamic aspect of topic and language over time. The dynamics in language used over time to indicate use of a frame needs to be modeled, because the specific words used to indicate the same topic, frame, or concept over time changes. The clearest example of this problem is the evolution of the

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To preprocess the text, English stop words were removed. To produce the document feature matrix, a normalized tf·weighting and unigrams are used. Additionally, any terms occurring in less than 10 documents were dropped.

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### Table 3: Summary of Change in Debate Structure (Frames and Frequency)

<table>
<thead>
<tr>
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<th>Min.</th>
<th>Mean</th>
<th>Max.</th>
<th>SD</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in Volume</td>
<td>-0.75</td>
<td>0.00</td>
<td>1.85</td>
<td>0.46</td>
<td>171.00</td>
</tr>
<tr>
<td>Change in Structure</td>
<td>0.21</td>
<td>0.69</td>
<td>1.50</td>
<td>0.27</td>
<td>171.00</td>
</tr>
<tr>
<td>Change in Debate</td>
<td>0.55</td>
<td>0.85</td>
<td>1.40</td>
<td>0.18</td>
<td>171.00</td>
</tr>
</tbody>
</table>
discussion and reference to race over time in the US; the words used to discuss and reference
African-Americans have changed drastically since the mid-1900s to today. In the end, each
speech is assigned a latent topic — frame — identified by the DTM. The benefit to this
approach over others is that the pool of possible topics that each document may contain is
the same for each Congress, and accommodates any potential linguistic drift within a topic.

When fitting the dynamic models, the number of topics \( k \) that maximized coherence
is chosen, and the number of topics searched over ranged from 10 to 50. For additional
information about the dynamic topic models themselves, see the appendix. This includes
information on the number of topics identified for each issue area by Congress and overall,
and the content of identified topics. From this process, I find that an average issue debate
contains 16 frames across the time period, and ranges from 10 frames (public lands) to 32
frames (defense). Note that the policy domains for the minimum and maximum number
of frames is different than those with the smallest and greatest number of speeches: the
number of speeches given does not correspond to the number of frames used. In fact, the
correlation between the number of speeches given and the number of frames detected is 0.08.
Additionally, the number of identified frames by issue area do not correlate with the number
of sub-issue areas associated with issue; the correlation between the number of frames and
number of sub-issue areas by issue area is 0.38. Instead of simply detecting general sub-issue
areas, the identified topics reflect something else: broad frames.

Second, I calculate the proportion of the speeches that predominately rely on each frame
for each issue area and Congress. For each Congress, this is simply the sum of the number of
speeches falling into each frame divided by the total number of speeches given on that issue
in that Congress. Third, I find the change in structure. This is done in the same manner the
change in structure was calculated in the example shown in Table 1. The absolute difference
between the proportion of documents invoking each frame from the current and previous
Congress is summed. Mathematically this is:

$$DS(A,B) = \sum_{i=1}^{k} |A_i - B_i|$$

(2)

In the equation, DS indicates debate structure, A is the vector of frame weights from the previous Congress, B is the vector frame weights from the current Congress, and k indicates the number of frames. This results in a score ranging from 0 to 2, where a score of 0 indicates that no change in frame use occurred and a score of 2 indicates that there is no shared frame between the two Congresses. As can be seen in Table 3, these values range from 0.21 to 1.50, and have a mean of 0.69.

To better illustrate what these scores look like, see Figure 4, which shows the measures for debate structure for health policy. The 12 possible frames identified for health policy are: quality of service, women as a vulnerable population, senior citizens as a vulnerable population, Congressional procedure, AIDS and world health, politics, morality and ethics, medical industrial complex, health legislation, children as a vulnerable population, reproductive health, and health insurance coverage. Many of these latent topics, frames, mirror frames found in the broader literature: classification of populations discussed by Schneider & Ingram (1993), universal frames discussed by Card, Boydstun, Gross, Resnik & Smith (2015), and morality frames as by Ryan (2014) or Armstrong (2003). Additionally, these latent topics seem to mirror what was found in by Pew in their reports on the health care debate in the 103rd and 111th Congress (Staff 2010, Clymer, Pear & Toner 1994). Playing politics maps onto the latent topics of Congressional procedure and politics. Discussion of the role of big government (the federal government) correlates with health legislation. Cost of programs corresponds with the burdens or lack thereof placed on the medical industrial complex. Additionally, the number of uninsured correspond directly with the health insurance coverage latent topic and more generally with the invocation of vulnerable populations (women, children, and the elderly).
Figure 3: Tracking Change in Debate Structure of Health Policy in Congress

![Graphs showing change in debate structure and frame use over time.](image)

(a) Change in Volume of Debate

(b) Change in Frame Use

Figure 4 demonstrates that there is variation in change in debate structure and change in attention. In the figure, two things should be noted. First, the spikes in each subfigure occur during the 111th Congress, when the Affordable Care Act was proposed and passed. This provides preliminary evidence that this theory framing may explain some amount of policy change. Second, the spike in change in frames used in subfigure 4a occurs because the number of frames used decreases: of the possible 12 only 8 are used at all, while typically ten are used.

Finally, these two independent measures are combined into a single measure by averaging the two together. The exact calculation for this is:

\[
\text{Debate} = \frac{\text{DS} + \frac{2 + \text{Volume}}{2}}{2}
\]

In the equation, DS indicates debates structure, and Volume indicates the change in volume. Volume is modified to shift the scale to range from 0 to 2 rather than -2 to 2 to put it on the same possible scale as debate structure. As seen in table 3, this results in a score that ranges from 0.55 to 1.40 and has a mean of 0.85. This is modeled as a single term rather
than as an interaction in the model to better align with the theoretical concept of change in debate overall.

**The Test**

Finally, because I only use the Congressional Record, I will test whether change in debate influences change in policy ideas considered (put to a vote) and passed. I do so because floor speeches can only directly speak to these two stages. To test these hypotheses, I fit two hierarchical linear models. The first predicts change in policy ideas voted on measured by the similarity in the language used in the bills proposed in the current and former Congress and the language used in the bills passed in the current and former Congress for a given issue area.

In these regressions, I control for whether the party in control of the House changes and whether the party in control of the Senate changes. Additionally, in the regression predicting change in policy ideas passed into law, I control for the change in policy ideas proposed in legislation; this should account for the degree of the debate dictated by what is proposed at least in part. These are included by switching of the parties might result in parties doubling down on pieces of legislation previously proposed but not passed. Additionally, some scholars point to a change in party in a chamber with greater policy change (Krehbiel 2010).

Finally, I include random intercepts for each Congress and fixed effects for each issue area. Random effects are included for each Congress to account for shocks to the system that may direct attention to either greater change across all issue areas or to that increase the similarity across all the issues. For example, the great recession may have influence the degree of similarity between bills between that Congress and the one before (greater change) and the that Congress and the one after (less change). Fixed effects for each issue area should capture the average churn in policy ideas in a given issue area. For example, if in the agriculture issue area, each Congress they cycle through different sub issue areas (ex. in one Congress agricultural subsidies are under consideration and in the next tariffs and
taxes but not subsidies are under consideration), then the average similarity in policy ideas will be consistently low. However, by including fixed effects this cyclical process producing artistically low values, I account for this systematic process.

**Changing Debate to Change Policy in Congress**

The resulting regressions are presented in Table 4. The first column presents the results of the regression explaining the similarity of ideas proposed in legislation; while the second column presents the results of the regression explaining the similarity of ideas passed into law. If we see the coefficient for change in debate is negative and statistically significant, then this would show that as the change in debate increases, the change in similarity of policy ideas decreases (meaning they are more different).

In table 4, we see support for the proposed relationship. For both the regression explain-

<table>
<thead>
<tr>
<th></th>
<th>Proposed Leg.</th>
<th>Passed Leg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.54**</td>
<td>0.55**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Change in Debate</td>
<td>−0.05**</td>
<td>−0.10**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Similarity in Proposed Legislation</td>
<td>−0.23</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td></td>
</tr>
<tr>
<td>Change in Party Control of the House</td>
<td>0.03**</td>
<td>0.03**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Change in Party Control of the Senate</td>
<td>0.02*</td>
<td>−0.00</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Issue Area Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>AIC</td>
<td>−400.98</td>
<td>−256.94</td>
</tr>
<tr>
<td>BIC</td>
<td>−328.40</td>
<td>−181.35</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>224.49</td>
<td>153.47</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>152</td>
<td>152</td>
</tr>
<tr>
<td>Num. groups: Cong</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>Var: Cong (Intercept)</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Var: Residual</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**p < 0.05, *p < 0.1
ing similarity in policy ideas in proposed legislation and explaining similarity in policy ideas in passed legislation, the coefficient for debate change is negative and statistically significant at the 0.05 level. For similarity in proposed policy in legislation, this means that the amount copied should decrease by 0.026 at the minimum level of debate change, by 0.043 at the mean level of debate change, and 0.07 by the maximum level of debate change. Alternatively, in terms of standard deviation, the mean change in debate results in a decrease of slightly less than one standard deviation of proposed bill similarity; the maximum change in debate, results in slightly over one standard deviation decrease. For similarity in passed policy in legislation, this is a decrease of 0.055 at the minimum of debate change, 0.085 at the mean of debate change, and 0.140 at the mean. Alternatively, in terms of standard deviation, the mean change in debate results in a decrease of almost one standard deviation of passed bill similarity; the maximum change in debate, results in slightly more than one standard deviation decrease. For further illustration, we can look at plots of this predicted relationship in Figure 5. In the figure, I assume no change in party control in either chamber and the policy area is macroeconomics.
In Figure 5, the change on debate is shown along the x-axis, and the similarity in policy is shown along the y-axis. The expected similarity is seen in the solid lines in each subfigure, while the dashed lines indicate the bootstrapped 95% confidence interval. The true distribution of the values of change in debate are presented along the bottom of the plot in the rug plot. Finally, the y-axis ranges from the minimum possible similarity for that legislative stage to the maximum value: for proposed legislation this is from 0.33 to 0.62; and for passed legislation, this is from 0.10 to 0.71. In each figure, the relationship can be more clearly be seen: as debate change increases, then the similarity of the policy ideas proposed and passed in legislation between the current and previous Congress decreases. Additionally, not only does the similarity of policy ideas between Congresses decrease, but they noticeably decrease.

To further put these results into substantive terms, take the debate on health policy once again. Between the 110th and 111th Congresses (the Congress immediately before the ACA was passed and the Congress in which the ACA was passed, the debate change measure was 1.33, the similarity in proposed legislation between the two Congresses was 0.61, and the similarity in passed legislation between the two Congresses was 0.22. Neither the House nor the Senate changed party control. Additionally, the health policy constant is 0.03 for proposed legislation and -0.03 for passed legislation. The predicted decrease in similarity of legislation proposed attributed to debate change is 0.07, and the predicted decrease in similarity of legislation passed attributed to debate change is 0.12.

Of the two control variables for change in party control of the House and of the Senate, change in party control of the House is consistently positive and statistically significant at the 0.1 level and is statistically significant at the 0.05 level for proposed legislation. One possible explanation of this result is that when a chamber switches majority party control, they attempt to amend and/or repeal what the previous Congress passed. This would require them to use much of the same language in the legislation they (the new members of the chamber) propose and pass, because they are focusing on the same (albeit opposing) policy ideas as what came before. Alternatively, this may be due to a doubling down by the
new party in power of the policies they proposed but did not pass in the previous Congress.

**Conclusion**

Does debate shift policy? I proposed that change in debate — the internal structure and the volume at which it is shouted — changes policy ideas proposed and passed in Congress. Using a unique data set of measures produced using the text of the Congressional Record and bills, I provided support for this claim when looking at both the legislation proposed and passed in a given Congress as compared to the one that came before. Debate on issues influences both what policies are proposed to address that issue and what policies are passed in legislation to address it. By showing support for the claim that debate structure influences change in policy ideas passed, I present and test one mechanism by which framing influences macro outcomes in a systematic way. Rather than emphasizing any single frame, I find some evidence that debate on an issue and changes to it influence policy outcomes.

Additionally, I have presented here a way to incorporate not simply whether a single frame is or is not used, but a single measure summarizing change in overall debate. I did so by first decomposing debate into two parts: structure and volume. Then I measured each — first with the use of dynamic topic models and then by calculating the percent change in speeches given — and combined the resulting measures into one. This produced a single, simple measure of how debate change.
Appendix

A Measuring Language Similarity in Bill Text Between Congresses

Policy change is operationalized as the change in policy ideas included in legislation between Congresses. The data for this comes from two places. I scraped the text of each bill included in the analysis from congress.gov. The policy codes come from the Congressional Bills Project\textsuperscript{7} and are the Comparative Agenda’s Policy codes. The discussion of the measure is divided into three subsections: 1) a brief discussion of the ratio of matches calculation itself; 2) a discussion of creating the similarity matrices for each policy area; and 3) the construction of the final measure of policy change between Congresses.

The Function: Ratio of Matches

Measuring the similarity in ideas has garnered increasing amounts of attention in political science and sociology. Researchers commonly do so either using algorithms that mimic plagiarism software or using genetic matching algorithms. In either case, researchers must also determine whether a directed or undirected measure should be used. Because a single bill may borrow from a portion of the entirety of another piece of legislation, for the analysis in this paper, a directed similarity function must be used. A directed similarity function calculates how much of one document matches that of another. Whereas an undirected similarity function calculates what amount of the total space is shared. A ratio of matches is a directed similarity function, which is what I use here. It produces a score that can be used to determine whether one document has plagiarized from another document. A ratio of matches function finds the ratio between the number of items in document \( b \) that are also

\textsuperscript{7}E. Scott Adler and John Wilkerson, Congressional Bills Project: 1993 to 2012, NSF 00880066 and 00880061. The views expressed are those of the authors and not the National Science Foundation.
in document a. The result is a number between 0 and 1, where 0 indicates no shared content and 1 indicates that document b only contains content from document a. Mathematically this is:

\[ M(a,b) = \frac{|a \cap b|}{|b|} \] (4)

As a result, this measure is directional; it measures how much b has drawn from a without saying how much a shares with b. To illustrate this, take the following three sentences:

1. Elizabeth is the queen of England, and she loves corgis.

2. Elizabeth is the queen of England.

3. She loves corgis.

A human reader easily sees that the three sentences share content and that the second and third sentences are almost exactly copied from the first. Using uni-grams (each word treated as a variable), we can calculate the ratio of matches between each potential pair. The scores attributed to each pair are seen in the table below.

<table>
<thead>
<tr>
<th>(Document a, Document b)</th>
<th>Statement 1</th>
<th>Statement 2</th>
<th>Statement 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statement 1</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Statement 2</td>
<td>0.60</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Statement 3</td>
<td>0.30</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

The above table shows that when compared to the first statement the second and third are completely copied. However, when compared to each other, the second and third are completely distinct. Additionally, the second column showing the amount statement 1 copied from the others varies, because each smaller statement only contains a portion of the overall sentence.
Similarity Between Bills

Because language in legislation is highly structured and constrained, plagiarism detection not only identifies strict plagiarizing, but also the more subtle transfer of policy ideas (Wilkerson, Smith & Stramp 2015). A single bill may borrow from a portion of another piece of legislation or another bill in its entirety. The borrowed portions may either be incorporated as a small section of the new piece of legislation or become the entire piece of legislation. As a result for this analysis, a directed similarity function must be used to accommodate this. To generate a measure of churn in policy ideas using bill text, I first generated a similarity matrix of all the bills proposed between 1993 and 2012 in R using the textreuse package (Mullen 2016). 5-grams (strings of five words) are used. This means that the ratio is the number of 5 word phrases shared between bill a and bill b divided by the number of 5 word phrases in bill b. The result is a series of matrices where each cell is the match ratio of two bills.

Similarity in Bills Between Congresses

To transform the matrices of comparisons into a single measure, I first assign a single similarity score for each bill. This assignment assumes that the degree to which one bill is similar to those proposed in the previous Congress is at most the maximum score assigned between when that bill was either in the “a” or “b” position in the calculation. As a result, if the given piece of legislation contains the entirety of two bills and a new portion, then the resulting score is still above 0.9. To generate a single score for each bill, I isolated the comparisons of that bill with all bills from the previous congress of that issue area. The score assigned is the maximum value from that vector. This is done for each bill.

With a single score per bill assigned, I then calculated the degree of change in policy ideas. It is calculated as the average bill similarity using the assigned scores. These calculations are done for each point in the process: proposed bills and bills passed into law. There are 82,215 proposed bills and 3,822 passed bills in the data set. On average for a given issue area in a given Congress, there are 526 (with a standard deviation of 359) bills proposed (with a
standard deviation of 54) and 24 passed into law (with a standard deviation of 24). To see the variation in these scores see figure 5. To see these scores over time and issue area, see figure 6.

**Figure 5: Density Plots of Average Change in Policy in Legislation**

(a) Proposed Legislation  (b) Committee Reported  (c) Passed Legislation

**Figure 6: Over Time Movement of Change in Policy Ideas**

*Note: Change is presented along the y-axis.*
B  Policy Coding the Congressional Record

To classify the Congressional Record according to policy area, I used the Comparative Policy Agenda’s coding scheme. Between the start of the 104th Congress (1995/1996) and the end of the 112th Congress (2011/2012), tens of thousands of speeches were logged in the Congressional Record. To hand code each according to CAP’s coding scheme would take years. Rather than code each document by hand, I used a combination of decision rules and machine learning to apply codes to the Record. Before cleaning and coding the Record, I scraped the Record from the Government Printing Office using a scraper that is variation on the Capital Words scraper originally written by the Sunlight foundation. From the raw documents, I generate topic codes in a series of two steps. These steps are: 1) merge in topic codes from Tyler Hughes’ data set for the one-minute floor speeches; and 2) using one minute speeches given on the floor of the House already coded according to the CAP policy codes, I trained a machine learning algorithm that can be used to code the remaining speeches.

Building the Corpus

I scraped the Congressional Record from the Government Printing Office. Then each speech is processed to the Congress, date of the speech, title of the speech, section of the record, and text of the speech. This was done in R. For further information about this process, please see the R code.

Many types of speeches are recorded in the Congressional Record ranging from readings of entire bills to the pledge of allegiance to actual debate about a piece of legislation. In this project, I am only concerned with those speeches that address a specific issue area; however, not all floor speeches even have the possibility of substantively being about a specific issue area. Rather, many speeches recorded in the Record are simply procedural. Thus, the first distinction that is made between the scraped speeches is between procedural and potentially substantive speeches. I tag procedural speeches based on their titles. Table B1 lists the titles
that are classified as procedural. As can be seen, these include such speeches as the morning prayer, the pledge of allegiance, and roll call.

Table B1: Procedural Speech Titles that are Excluded

<table>
<thead>
<tr>
<th>Chamber</th>
<th>Procedural Speeches</th>
</tr>
</thead>
<tbody>
<tr>
<td>House</td>
<td>ANNOUNCEMENT BY THE SPEAKER PRO TEMPORE; THE JOURNAL RECESS; AFTER RECESS; ADJOURNMENT; PRAYER; PLEDGE OF ALLEGIANCE; EXECUTIVE COMMUNICATIONS; ETC.; CONSTITUTIONAL AUTHORITY STATEMENT; PUBLIC BILLS AND RESOLUTIONS; ADDITIONAL SPONSORS; HOUSE OF REPRESENTATIVES; REPORTS OF COMMITTEES ON PUBLIC BILLS AND RESOLUTIONS; LEAVE OF ABSENCE; COMMUNICATION FROM THE CLERK OF THE HOUSE; MORNING-OUR DEBATE; DESIGNATION OF SPEAKER PRO TEMPORE; ORGANIZATION OF THE SPEAKER PRO TEMPORE; PDF:/a; PERSONAL EXPLANATION; ANNOUNCEMENT BY THE SPEAKER; CONGRESSIONAL EARMARKS; LIMITED TAX BENEFITS, OR LIMITED TARIFF BENEFITS; MESSAGE FROM THE SENATE; MEMORIALS, AMENDMENTS; DELETIONS OF SPONSORS FROM PUBLIC BILLS AND RESOLUTIONS; GENERAL LEAVE; HOUR OF MEETING ON TOMORROW; SENATE; ENROLLED BILL SIGNED; HURRICANE SANDY RELIEF; SENATE BILL REFERRED; LEGISLATIVE PROGRAM; EXPENDITURE REPORTS CONCERNING OFFICIAL FOREIGN TRAVEL; PETITIONS AND MEMORIALS; PRAYER; PLEDGE OF ALLEGIANCE; EXECUTIVE COMMUNICATIONS, ETC.; CONSTITUTIONAL AUTHORITY STATEMENT; [ ]</td>
</tr>
<tr>
<td>Senate</td>
<td>ADDITIONAL SPONSORS; ADDITIONAL STATEMENTS; ADJOURNMENT OR RECESS OF THE HOUSE AND SENATE; ADJOURNMENT UNTIL, AMENDING SENATE RULES; AMENDMENTS SUBMITTED AND PROPOSED; APPOINTMENT; AUTHORITY FOR COMMITTEES TO MEET; AUTHORIZING APPOINTMENT OF A COMMITTEE TO ESCORT THE PRESIDENT OF THE UNITED STATES; AUTHORIZING APPOINTMENT OF ESCORT COMMITTEE; AUTHORIZING THE USE OF THE EMANCIPATION HALL; AUTHORIZING THE USE OF THE ROTUNDA; AUTHORIZING USE OF THE ROTUNDA; BEGINNING THE; BUDGET NEGOTIATIONS; CERTIFICATES OF ELECTION; CONCLUSION OF MORNING BUSINESS; CONFIRMATION; CONTINUING RESOLUTION; DISCHARGED NOMINATIONS DISCHARGED; NOTICE OF INTENTION TO OBJECT TO PROCEEDING; NOTICE OF ISSUANCE; NOTICE: REGISTRATION OF MASS NOMINATIONS DISCHARGED; NOTICE OF HEARING; NOTICE OF HEARINGS; NOTICE OF INTENT TO OBJECT; ORDER OF BUSINESS; ORDEAL OF PROCEDURE; ORDERS FOR; PDF:/a; PERSONAL EXPLANATION; ANNOUNCEMENT BY THE SPEAKER; CONSTITUTIONAL AUTHORITY STATEMENT; [ ]</td>
</tr>
</tbody>
</table>

Once purely procedural speeches have been separated out, I then narrow the number of possible speeches to classify in two ways. First, all of the one-minute speeches given on the floor of the House have already been classified for this period by Tyler Hughes (Hughes 2016).
Two codes are taken from his dataset: whether or not the one-minute speech is on an issue area; and which issue area the speech addresses if any. Second, I identify which speeches are not on policy but rather remember, recognize, honor or commend individuals, groups, organizations, or events. These speeches do not need to be policy coded.

**Supervised Classification Using One Minute Floor Speeches**

The already coded documents come from Tyler Hughes’ (Hughes 2016) data set of Congressional one-minute speeches given on the House floor between the 101st (1989/1990) and 112th Congress (2011/2012). There are 43,859 speeches, each of which is given one of twenty-one codes. The twenty-one codes consist of a non-policy code and the twenty major topic codes in the CAP codebook. Of these speeches, just over 11,000 were coded by hand, while the remaining documents were assigned codes based on a machine learning algorithm.

To construct the classifier to apply codes to the remaining documents, I mimic the process done by Hughes. First, documents are classified as being about any policy or not. Then, those documents identified as being about any policy are classified for what policy they discuss. For each stage, I use a linear SVM as implemented as a part of the e1071 package in R. A stratified random sample of 625 documents each is drawn for the following areas: no policy discussed, macro economics, civil rights, international affairs, and government operations. A stratified random sample of 125 documents each is drawn for the remaining areas. These are: health, agriculture, labor, education, environment, energy, immigration, transportation, law and crime, social welfare, housing, banking, defense, science and technology, foreign trade, and public lands. This results in a training set of 5625 documents for the first process and 5000 documents for the second process. In each case, there is a testing set of 38,234 documents. The training set of documents is used to fit the classifier. The testing set of documents is used to evaluate the classifier.

The first stage, whether or not a document is about a policy at all, has a 95.31% accuracy, which is almost 10% better than if the computer had simply classified every document as
being about a policy. The second stage, which policy it is about, has a 80.26% accuracy. There are many ways to interpret whether this is sufficiently good enough. First, if accuracy is treated as a test of inter-coder reliability such as the calculation of Cohen’s alpha, then this would pass the arbitrary threshold for use (0.8). Alternatively, this could be compared to what the computer would do if topics were randomly assigned. If all were equally likely, then by random assignment and perfect classification in the previous step, then the accuracy of guessing at would be 5%. In both cases, it passes the bar. With the built classifier and built corpus, the topics were then applied. This process was completed in R.

C Dynamic Topic Models and the Congressional Record

To measure debate structure, I identify frames used in each issue area using a series of dynamic topic models. The specific implementation used was written and developed by Greene & Cross (2017); it uses non-negative matrix factorization to do so. There are four steps in estimating the latent frames. First, the text must be pre-processed. Within pre-processing, first the Word2Vec associations between the terms in all the documents is created, and then the text is transformed into a document-term matrix. In a document-term matrix, the documents make up the observations and the terms make up the variables. The values are the representation of the text. In this case, English stop words were removed from the documents, a normalized tf-idf (term frequency-inverse document frequency) representation was used, terms appearing in less than 10 documents were removed, and uni-grams are used. This is done individually for each issue area. Second, a topic model for each time period, in this case each Congress, is fit for each issue area. At this stage the number of potential frames allowed to emerge ranged from 10 to 50. To choose the number of frames, I simply choose the number of frames that maximizes coherence (a measure of model fit). The optimal number for an issue and Congress is seen in Table 6.

Third, using the individually fit topic models, the number of frames across the time
windows (across the Congresses) needs to be identified. To do this, once again the maximum coherence is used. The result of this is often the number of overall frames detected in the entire corpus is less that the number in any given Congress. This number for each issue area is seen in the second to last column. Finally, frames are assigned to every document, and the top terms for each identified frames are output.

Table 6: Number of Identified Topics by Congress and Overall

<table>
<thead>
<tr>
<th>Issue Area</th>
<th>104</th>
<th>105</th>
<th>106</th>
<th>107</th>
<th>108</th>
<th>109</th>
<th>110</th>
<th>111</th>
<th>112</th>
<th>All</th>
<th>Doc.</th>
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<tbody>
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<td>10</td>
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D Alternative Specification for the Regressions

Alternatively, the measure of change in debate can be decomposed to its two component parts and interacted. The resulting regressions are presented in table 7. The first column presents the results of the regression explaining the similarity of ideas proposed in legislation; while the second column presents the results of the regression explaining the similarity of ideas passed into law. Support for the proposed hypotheses is seen if the change in frame use
and percent change in volume variables are negative and statistically significant. While the true values of each of these coefficients can be seen in table 7, they are misleading, because the change in frame use is interacted with percent change in volume to fully capture change in debate structure. To do so, I turn to conditional effects plots of the variables for each regression. Figure 9 shows the conditional effect of change in frame use on similarity of policy ideas. Figure 10 shows the conditional effect of percent change in volume on similarity.

In figure 9, the estimated coefficient for change in frame use is shown on the y-axis, while the percent change in volume is shown on the y-axis. The horizontal line in each subfigure indicates zero. The sloping solid lines indicate the estimated coefficient, and the gray shaded area indicates the 95% confidence interval. Subfigure 9a shows no support for the proposed hypotheses: across the entire range of possible coefficients for change in frame use statistically significantly distinct from 0 at the 0.05 level. However, while support for the hypotheses concerning change in frame use and proposed legislation is not found, a different story emerges for passed legislation.

Subfigure 9b shows the estimated coefficient for change in frame use across the range of values the variable percent change in volume can take on. I hypothesized that a negative relationship should exist between the two variables, which is seen in the figure: the line slopes down. Additionally, the figure shows that change in frame use is conditionally statistically significant. If percent change in volume is greater than approximately 0.5, then increased change in frame use decreases the similarity of passed policy ideas. In other words, as debate changes, the policy ideas enacted change.

In figure 10, the estimated coefficient for percent change in volume is shown on the y-axis, while the change in frame use is shown on the y-axis. As in the previous set of figures, the horizontal line in each subfigure indicates zero. Additionally, the sloping solid lines indicate the estimated coefficient, and the gray shaded area indicates the 95% confidence interval. Subfigure 10a does not support for the proposed hypotheses: at almost no point is the possible coefficient for percent change in volume statistically distinct from 0 at the 0.05 level.
Table 7: Explaining Change in Policy Ideas, Alternative Specification

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<td>0.39**</td>
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<td>Change in Volume</td>
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<td></td>
<td>(0.03)</td>
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<td>Change in Party Control of the House</td>
<td>0.03**</td>
<td>0.03**</td>
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<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
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<tr>
<td>Change in Party Control of the Senate</td>
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<td>AIC</td>
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<td>Var: Residual</td>
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**p < 0.05, *p < 0.1

level. As before, a different story emerges for passed legislation.

Subfigure 10b shows the estimated coefficient for percent change in volume across the range of values the change in frame use variable can take on in the data. As with change in frames used, I hypothesized that a negative relationship should exist between the two variables, which is seen in the figure: the line slopes down. Additionally, the figure shows that change in frame use is conditionally statistically significant. If change in frames used is greater than a little over 0.3, then increased change in volume decreases the similarity of passed policy ideas. In other words, we same the same pattern: as debate changes, the policy ideas enacted change. Between these two tests then, I find support for my hypotheses for passed legislation, but not for proposed legislation.
Figure 7: Conditional Effect of Change in Frame Use on Change in Policy Ideas

(a) Proposed Legislation
(b) Passed Legislation

Figure 8: Conditional Effect of Percent Change in Volume on Change in Policy Ideas

(a) Proposed Legislation
(b) Passed Legislation
References


Annas, George J. 1995. “Reframing the debate on health care reform by replacing our metaphors.”.


